OPTIMAL DECISION-MAKING OF LARGE-SCALE MULTI-STATE INFRASTRUCTURES CONSIDERING SYSTEM PERFORMANCE UNCERTAINTIES AND MEASUREMENT RANDOMNESS

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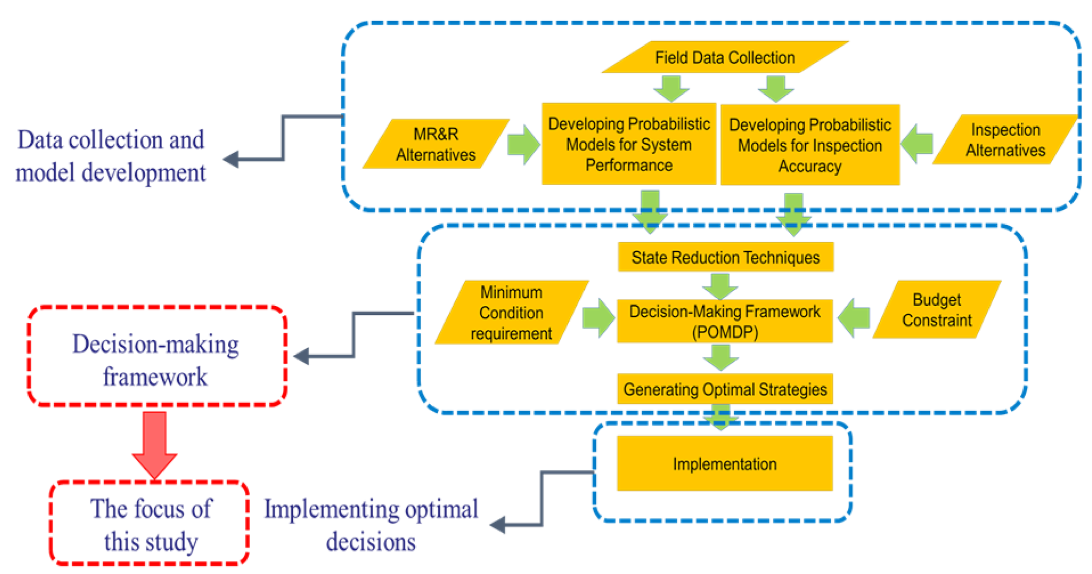
Introduction

Infrastructure systems play a critical role in providing continuous services to societies. However, these complex systems are exposed to a number of challenges that threaten the functionality and safety of these systems:

- aging, continuous demand loads, and environmental stressors,
- and uncertainties in the performance of the system, and within inspection results.

Therefore, for proper management of infrastructure systems, comprehensive probabilistic decision-making frameworks are

Infrastructure Systems Management



Although Markov Decision Processes (MDPs) provide capable probabilistic frameworks to incorporate uncertainties in system behavior, they suffer from these shortcomings:

1. measurement randomness arising from imperfect inspections is disregarded in those models.
2. for large scale multi-state multi-component systems, the scale of the decision-making problem increases exponentially with respect to the number of system components. E.g. for a system consisting of 10 components each having 9 condition-states, there exists 9^{10} state combinations!

Aims

To develop a comprehensive decision-making framework that enables assigning optimal decisions of inspection, maintenance and repair throughout the lifetime of infrastructures. It should

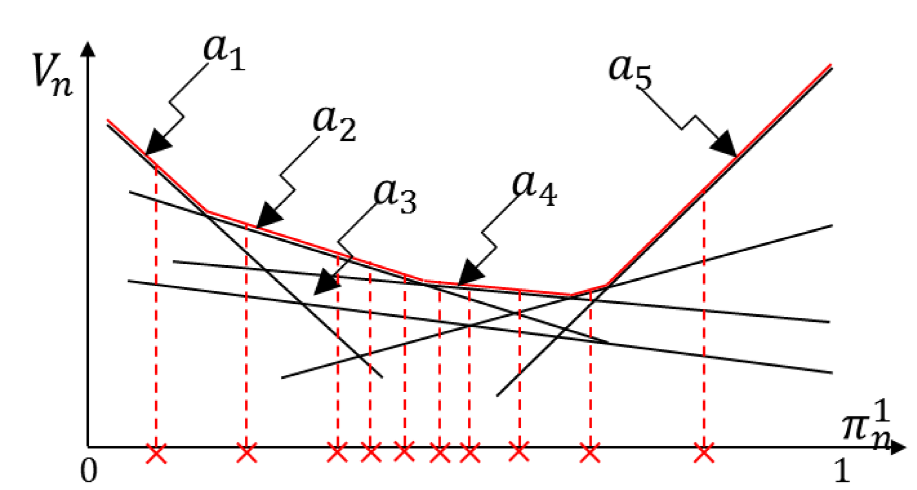
- minimize the expected costs imposed on users and agencies.
- be practical for large-scale multi-state multi-component systems.
- enable component-level optimal decisions.
- integrate the uncertainties in system performance and inspection evaluations.

Methods

A fast steady-state algorithm able to integrate system performance and measurement randomness in the decision-making framework is employed and adapted: **Randomized value-iteration Partially Observable Markov Decision Process** (POMDP) (called Perseus).

$$V_n = max_{a_n}\left\{\overrightarrow{\pi_n^{\acute{s}}}.\left[\overrightarrow{r_{a_n\acute{s}}} + \gamma \sum_{o}\sum_{\acute{s}} \alpha_{\pi^{\acute{s}}}^{i,n-1^*} \times P(o_{n-1}|\acute{s}_{n-1}, a_n) \times \vec{P}(\acute{s}_{n-1}|a_n, s_n)\right]\right\}$$

where $\overrightarrow{\pi_n^{\acute{s}}}$ (belief point) is a probability distribution over the true states at stage n. In Perseus, a set of likely belief state points (×) is determined through random walks, and optimal decisions are derived for these points.



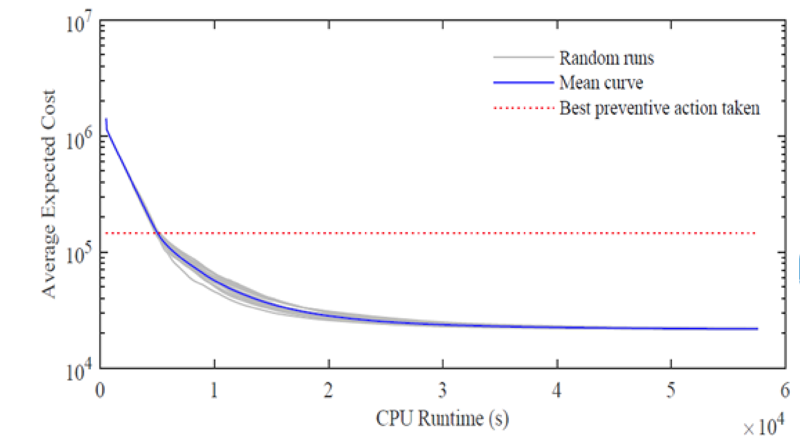
Perseus algorithm for a 2-state ($|S|=1$), 1-component ($N=1$) system

For large-scale multi-state multi-component systems, a **counting process technique** is proposed to reduce the size of states: Components with similar structural features, damage consequences, and state transition probabilities are grouped together. Then, instead of considering all possible combinations of condition-states, the new condition-states, called **Super States**, represent the quantity of components in a specific state. Number of states is reduced from $|S|^N$ to $\binom{N+|S|-1}{|S|-1}$, yet optimal decisions are in component level, made for all components in each of the condition-states.

Results

The framework was implemented on a bridge system with four steel girders and a concrete deck with realistic data. Using the proposed framework, the total number of states reduced from 3125 to 350. Also, the Perseus algorithm enabled the decision-making framework to figure out optimal decisions among 2160 action combinations in less than 16 hours on OSC (Ohio Supercomputer Center) cores.

Due to the inherent randomness of Perseus, the analysis was performed 20 times to explore its robustness. The 20 random runs converged and showed low variation, indicating robustness.



Optimal Policy Tag	Belief Point Frequency	Policy description							
		Optimal action						Optimal inspection strategy for the following year	
		Girders in State 1	Girders in State 2	Girders in State 3	Girders in State 4	Girders in State 5	Concrete deck	Girders	Concrete Deck
1	7	DN	DN	DN	DN	DN	DN	VI	VI
9	12	DN	DN	RP	RP	DN	DN	VI	VI
14	5	DN	DN	RP	DN	MR	DN	VI	VI
15	28	DN	DN	RP	RP	DN	DN	VI	VI
37	21	DN	CP	DN	DN	DN	DN	VI	VI
45	1941	DN	CP	RP	RP	DN	DN	VI	VI
50	6929	DN	CP	RP	DN	MR	DN	VI	VI
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
52	231	DN	CP	RP	RP	MR	DN	VI	VI
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
103	31	SC	CP	RP	DN	DN	DN	VI	VI
107	49	SC	CP	RP	SCP	DN	DN	VI	VI
157	1	DN	CP	RP	DN	DN	RSD	VI	VI
202	7	SC	CP	RP	DN	MR	RSD	VI	VI
215	8	SC	CP	RP	SCP	DN	RSD	VI	VI
216	1	SC	CP	RP	SCP	MR	RSD	VI	VI

Note: DN=Do Nothing, RP=Replace Paint system, MR=Major Rehabilitation, CP=Clean and Paint, SC=Surface Clean, SCP=Spot blast, CP=Clean and Paint, RSD=Repair Spalls and Delaminations, DNO= Do Not Observe, VI= Visual Inspection, HP=Half-cell Potential inspection

Long-run expected cost for 20 sample runs and

Optimal actions for a sample run

Optimal strategies were investigated for a random run with 10000 Belief Points (BPs). 16 different optimal actions were derived for these BPs. Based on the history of actions and observations, the BP of the system can be derived using Bayes rule. Then, it will be mapped to the best of the 10000 BPs. Consequently, the corresponding optimal action for this likely BP will be the optimal strategy to take for the BP of the system at the current time.

Conclusion

A probabilistic decision-making framework is proposed that enables element-level decision-making of large-scale multi-state multi-component infrastructures through integrating:

- a randomized value iteration POMDP, which incorporates system performance and observation uncertainties into the decision-making framework, and
- a proposed counting process state reduction technique, where instead of all the combinations of components' condition-states, the quantity of the components in each of the states is considered.

The proposed framework is general and can be implemented for optimal decision-making of any multi-component system.

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